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Evaluating stability of underground entry-type excavations using multivariate adaptive regression splines and logistic regression

Anthony T.C. Goh[c], Yanmei Zhang[d], Runhong Zhang[a,b], Wengang Zhang[a,b,*], Yang Xiao[a,b]

[a] Key Laboratory of New Technology for Construction of Cities in Mountain Area, Chongqing University, Chongqing 400045, China
[b] School of Civil Engineering, Chongqing University, Chongqing 400045, China
[c] School of Civil and Environmental Engineering, Nanyang Technological University, 639798, Singapore
[d] School of Mechanical and Aerospace Engineering, Nanyang Technological University, 639798, Singapore

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ABSTRACT

The mining industry relies heavily on the use of empirical methods and charts for the design and assessment of entry-type excavations. The commonly adopted empirical design method, commonly referred to as the critical span graph, which was specifically developed for the assessment of rock stability in entry-type excavations, was based on an extensive database of cut and fill mining operations and case histories in Canada. It plots the critical span versus the rock mass rating for the observed case histories and has been widely accepted for an initial span design of cut and fill stopes. Different approaches, either based on classical regression and classification statistical techniques or even the supervised machine learning methods, have been proposed to classify the observed cases into stable, potentially unstable and unstable groups. This paper presents a new assessment approach which combines the use of a multivariate adaptive regression splines (MARS) approach and the logistic regression (LR) method. The proposed MARS_LR model can capture and describe the intrinsic, complex relationship between input descriptors and the dependent response without having to make any assumptions about the underlying relationship. Considering its simplicity in interpretation, predictive accuracy, its data-driven and adaptive nature plus the ability to map the interaction between variables, the use of MARS_LR model in evaluating stability of underground entry-type excavations is promising.

1. Introduction

In many mining operations, the entry-type mining methods, such as cut and fill, have been replaced by less expensive, non-entry mining methods. In many mines, however, cut and fill is still indispensable in conditions where the hanging wall is very weak or ore body contacts are quite irregular. Therefore, entry-type mining methods are still desirable. However, in view of the relatively high costs associated with this mining method, there could be significant savings from an improved, more reliable and safe, back stability design (Wang et al., 2000).

There are many empirical and numerical methods for assessing the back stability of entry-type underground openings. It is generally difficult to obtain reliable input data describing the rock mass conditions for numerical approaches, for which the mechanical parameters are usually derived from rock mass classification systems such as the tunneling quality index (Q) system, rock mass rating (RMR) system, and the geological strength index (GSI) system, through empirical equations based on cases from various parts of the world. Furthermore, the numerical approach is computationally more expensive to carry out. In a production environment, a quick and reliable design method that can give the field engineers or technicians safe guidelines for opening dimensions is of critical importance. This paper looks at some of these empirical design approaches. Based on the collection of field data and an assessment of stability, usually these approaches can only be reliably used in conditions similar to those under which the empirical data sets were collected.

The most widely used empirical design method called the "critical span graph" was developed by Lang (1994) to provide a practical design tool specifically for spans in entry-type excavations. It is based on an extensive database of cut and fill mining operations and case histories in Canada. This graph defines stable, potentially unstable and unstable cases in span areas on a plot of RMR (Bieniawski, 1976) (RMR_{76} rock mass performance parameter) against the span between pillars. It has been accepted in many mining operations for a preliminary span design and enables a design engineer to assess the stability of mine openings with respect to an in situ rock mass condition. Recently, García-Gonzalo et al. (2016) adopted the supervised machine

* Corresponding author at: School of Civil Engineering, Chongqing University, Chongqing 400045, China.
E-mail address: cheungwg@126.com (W. Zhang).

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learning classifiers (support vector machine and extreme learning machines) to define stability areas of the critical span graph. Although the predictive capacities of these two models are satisfactory, they have been criticized for the computational inefficiency and poor model interpretability.

A new assessment approach which combines the use of a multivariate adaptive regression splines (MARS) approach and the logistic regression (LR) method is proposed in this paper. The following Section 2 reviews the critical span graph and the database development. Section 3 describes the multivariate adaptive regression splines (MARS) approach and the logistic regression (LR) method, as well as the evaluating criterion for a pattern-classification model. Section 4 explains how the method is applied and the modeling results. Major and significant conclusions arrived in this study are summarized in the Section 5.

2. Critical span graph

The critical span graph developed by Lang (1994) was specifically used for initial span design, by compiling and plotting the 172 observations of a database from entry-type case histories, on a span versus RMR_{76} graph, to enable prediction of stable spans given the RMR_{76} of the stope (García-Gonzalo et al., 2016). RMR_{76} is widely accepted and used as a rock mass classification system, combining the most significant geomechanical parameters and representing them with an overall comprehensive rock mass quality index. Considering that the RMR system has been updated several times since its first publication, it is generally referred to with a subscript indicating the year to identify the version being used. As an example of RMR_{76} application in characterizing the rock mass, the mean values of the different geologic parameters and the resulting index values are shown in Table 1 for the two main areas of the operation of the Detour Lake Gold Mine (Lang, 1994), where the original database values compiled by Lang (1994) were obtained.

The critical span graph developed by Lang (1994) consists of two straight lines that divide the RMR_{76} versus span graph into three different stability zones (stable, potentially unstable and unstable rock), as shown in Fig. 1.

In 2002, the database was expanded to 292 observations through a further investigation conducted by Wang et al. (2002), with inclusion of case histories from an additional six more mining operations and using a neural network analysis for reconstruction of the stability graph to update the critical span graph. Subsequently Kumar (2003) incorporated 107 more new observations for a final database with 399 cases in all, and updated the critical span graph also using a neural network approach. Since the database established in the work of Kumar (2003) incorporates the largest number of cases, it is taken as the reference for conducting the present study. In brief, this final database consisted of stope behavior data from eight operating mines in Canada with observational data from 399 operational case histories. The data case history sources are summarized in Table 2. Each case history contains an RMR_{76} value, span and the corresponding stope stability condition.

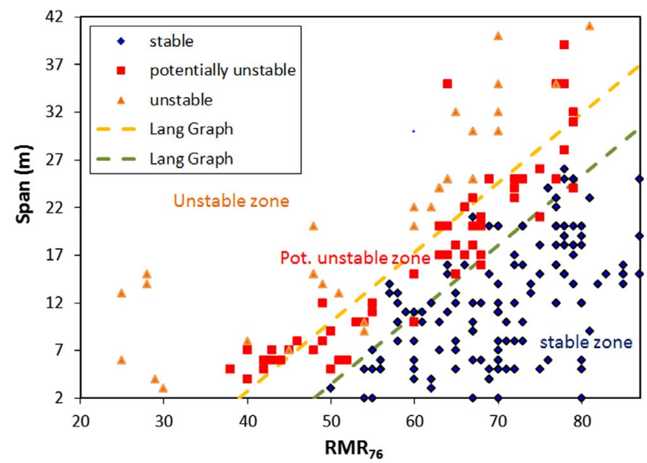

Fig. 1. Critical span graph.
Adapted from Lang (1994).

In this database, RMR_{76} ranges from 24 to 87 and the span varies from 2 to 41 m. The RMR_{76} values for 57% of the cases concentrated in the range of 60–80 while the span values from 3 to 30 m constitute 95% of the cases. The input data were obtained from different mines that had different personnel surveying the stope dimensions and estimating the RMR_{76}. This brought in huge variability or inaccuracy into the input data. However, the span estimation error should be substantially below 1 m, which is within the tolerance of the graphical design approach. On the other hand, the variability in estimating RMR_{76} value could be more significant and largely depends on the level of experience of the engineer conducting this classification work. The critical span graph and its updates have been widely accepted in the mining industry and provide a quick and simple tool to estimate a maximum span that might be designed based on the observed RMR_{76} value.

Almost all previous work with the critical span graph classifies the data into three groups, since the field observations are grouped into the stable, unstable and potentially unstable categories. García-Gonzalo et al. (2016) considered an alternative construction of the critical span graph, requiring only the information of field observations corresponding to the stable and unstable classes, using a probabilistic classification that allows one to define soft boundaries between the two classes considered. As these two classes are easier to assess by the engineer, the error due to incorrect assessment can thus be minimized. This paper uses the MARS_LR approach to probabilistically define the soft boundaries between the stable and unstable cases.

Table 1
RMR_{76} at Detour Lake Mine.
Adapted from García-Gonzalo et al. (2016).

Category	Main zone		Talc zone	
	Description	Rating	Description	Rating
Strength (MPa)	160–180	13	35–50	4
RQD (%)	90	17	80	16
Joint spacing (m)	0.4	16	0.3	9
Joint Condition	Smooth, hard, tight	17	Smooth surfaces, soft	10
Groundwater	None	10	None	10
Joint Orientation		0		0
Total RMR_{76}		73		49

Table 2
Data sources of the case histories.
Adapted from Kumar (2003).

Mines	Cases	Stable (S)	Potentially unstable (P)	Unstable (U)
Detour Lake Mine	172	94	37	41
Detour Lake Mine	22	10	0	12
Photo Lake Mine	6	0	6	0
Olympias Mine	13	4	1	8
Brunswick Mining	17	5	3	9
Musslewhite Mine	46	35	10	1
Snip Mine	16	12	2	2
Red Lake Mine	107	81	19	7
Summary	399	241	78	80